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WIND DIRECTION PREDICTION USING NEURAL NETWORKS - A PRELIMINARY STUDY

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This report summarizes the results of a preliminary investigation on the feasibility of using neural networks for the prediction of wind direction in the neighbourhood of Ontario Hydro's nuclear generating stations. The predictions are consistently better than those based on wind persistence, but the improvement is only about 1 to 5 percent. There is reason to believe that the datasets used for training have not been statistically adequate and recommendations for further work focus primarily on overcoming this shortcoming.

1. INTRODUCTION

Nuclear Emergency response procedures require meteorologists to forecast local meteorological conditions at various sites in the province, for use in case of an emergency. One of the variables to be predicted is the wind direction over the four hour period one to five hours in the future. At the request of the System Operation Department, an investigation on the potential of using neural networks for predicting the local wind direction is being conducted. This report summarizes the work to date.

2. THE NEURAL NETWORK APPROACH

The neural network approach is a biologically motivated statistical method for mapping between vector spaces. It has been proven that any arbitrary continuous mapping between two vector spaces can be

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realized using a neural network. In recent years, the approach has been used successfully in many pattern recognition applications, where a neural network maps an input pattern vector into an output decision vector. There have also been a number of investigations into the use of neural networks for many non-linear modelling applications. In the modelling case, the problem is one of finding an approximation to a mapping from an input vector (independent variables) to an output vector (dependent variables). A distinctive feature of a neural network is that there is no algorithmic analysis of the problem, but the network is 'trained' by showing it samples of the desired mapping. Neural networks are particularly useful in cases where the data is noisy, as long as a statistically valid set of example data is available for training. Advantages over traditional methods such as regression approaches include the fact that the neural network method makes only minimal assumptions of any functional relationships between the dependent and independent variables.

A neural network consists of an array of interconnected elementary processors (or neurons). The most popular model is called a multi-layer perceptron, where the network is arranged in layers, consisting of an input layer, one or more hidden layers and an output layer. Each neuron in a layer is connected to every neuron in the neighboring layer with distinct interconnection weights. A network performs an input-output mapping as follows. A signal representing the input vector is presented to the input layer. The activation level of each neuron in the other layers is a simple function of the weighted sum of the activation levels of the neurons in the prior layer. The activation levels of the neurons in the output layer represent the output vector. The hidden layer usually represents the key to the proper mapping by capturing functional representations that are not obvious in the input variables.

The network starts with random weights and the weights are adapted, ie, the network is 'trained' to realize the appropriate mapping by showing it examples of the proper mapping. The commonly used adaptation algorithm, called the back-propagation algorithm (Rumelhart, Hinton and Williams, 1986), is used in this study. It uses the gradient descent method to minimize the sum of the squared error at the output layer between the actual output and the expected (or target) output over all the training cases.

3. CURRENT STUDY

This study involves a preliminary investigation of the use of neural networks to predict the wind direction based on the 1988 MESONET data from Pickering. Although the emergency response procedures require forecasts one to five hours in the future, this part of the study focusses on forecasts only one hour in the future. Extensions to forecasts further in the future are conceptually straightforward. At the suggestion of personnel from the System Operation Department, the prediction is limited to cases where the synoptic category remains constant. Synoptic categories are numbers assigned based upon information derived from weather maps, (see Ogram and Middleton, 1991) and are listed in Table I.

The method attempts to approximate the future wind direction as a function of the past values of variables listed in Table II. Each independent variable is normalized to the range [0,1], ie,

$$x_n = (x - x_{min}) / (x_{max} - x_{min}) .$$

As indicated in the table, some variables are termed 'cyclic'. A cyclic variable cannot be input directly (eg, wind directions of 359° and 1° are only 2 degrees apart) and some transformation is needed . In this study, each cyclic variable is represented by two values and transformations based on arcsin(sin) and arcsin(cos) are used.

Several combinations of training/test subsets were studied. The results shown refer to the case where the predictor is trained using the data for June and July and is tested on the data for August. (The synoptic category was more 'volatile' during other months with the result that very few training cases were available). Several variations were also studied including: use of polynomial functions of the variables, use of trigonometric functions of the variables, discretization of the wind direction and ignoring wind direction changes over 90^{0}. But the results were not significantly different from those reported below.

Data at t, t-1 and t-2 used to predict the wind direction at t+1 and the results are summarized in Tables III and IV.

4. CONCLUSIONS

4.1 Summary of Results

Table III lists the success rates using the neural network predictor and the persistence based predictor, which assumes that the wind direction remains the same as the previous hour. The results shown are for August 1988 for three synoptic categories. A prediction is defined as a success if the absolute difference between the predicted value and the actual value is less than a predetermined number α. Predictions using the neural network model are better than those using a persistence based predictor, but the improvement is only marginal (1% to 5%). Table IV lists the correlation coefficients between the predicted and the actual values, using the two predictors. It is interesting to note that the correlation coefficient is quite high for both the predictors. Figure 1 shows the scatterplots of the wind direction (neural network prediction vs actual value) for the three synoptic categories. It can be seen that the performance is independent of the actual value of the wind direction.

The encouraging factor in the results is that the neural network model performs consistently better than the persistence based predictor for all the three synoptic categories studied and for all the three values of the success code parameter chosen. That is, a pattern defining the wind direction in terms of the values of certain variables over the previous three hours does exist, and the neural network has been successful in capturing at least some of the pattern. However, the performance is clearly not as impressive as was expected. There is reason to believe that the primary factor is the shortage of training data. That is, the training set has not included an adequate statistical representation of the test set. This is further borne out by the fact that the best results are obtained for the case when the maximum number of data points are available (synoptic category=4).

4.2 Recommendations

Recommendations for further work focus primarily on improving the statistical adequacy of the training dataset and are listed below. There is reason to believe that this additional work will result in a predictor with much improved performance. Note that some of the work can be accomplished with the existing data, while the others (the last two) will involve considerable additional data preparation.

- Training across synoptic categories with synoptic category as an indicator variable. This will increase the number of records available for training
- Predictions two to five hours in the future. Preliminary indications are that in these cases, improvements over the persistence based predictor is more significant
- Alternative coding of cyclical data (eg, cartesian coordinates, trigonometric functions)
- Smoothing of the measured wind direction before training or testing
- Use of other predictors (eg classical statistical methods)
- Use of data from neighbouring stations
- Use of data from other years (to get more training points).

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TABLE I - SYNOPTIC CATEGORIES

Category	Description
1	The warm sector of an extratopical cyclone with cyclonic curvature of surface isobars
2	The region ahead of a warm front with cyclonic curvature of surface isobars
3	The region behind a cold front with cyclonic curvature of surface isobars
4	Under the influence of a cold core ridge with anticyclonic curvature of surface isobars
5	Under the influence of a warm core subtropical ridge with anticyclonic curvature of surface isobars

TABLE II - INDEPENDENT VARIABLES

Variable (Hourly Data)	Yearly Minimum	Yearly Maximum
Julian Day[1]	0	365
Hour of day[1]	0	24
Mean Scalar Wind Speed (m/s)	0	10
Standard Deviation of Scalar Wind Speed (m/s)	0	2
Maximum Scalar Wind Speed (m/s)	0	20
Mean Vector Wind Speed (m/s)	0	10
Wind Direction[1] (degrees)	0	360
Standard Deviation of the Wind Direction (degrees)	0	50
Air Temperature (^{0}C)	-30	30
Barometric Pressure (kPa)	96	102
Orientation of the Surface Isobars[1]	0	8

[1] a cyclic variable

TABLE III - SUCCESS RATES

Synoptic Category	Success Rate Parameter α[2]	Neural Network Predictor	Persistence Based Predictor	Improvement Using Neural Networks
3 (n=94)[1]	22.5^0	83.0%	82.0%	1.0%
	15.0^0	76.6%	75.5%	1.1%
	7.50^0	58.5%	56.4%	2.1%
4 (n=229)	22.5^0	79.0%	75.3%	3.7%
	15.0^0	69.4%	64.6%	4.8%
	7.50^0	50.5%	48.5%	2.0%
5 (n=147)	22.5^0	72.8%	70.1%	2.7%
	15.0^0	64.6%	61.9%	2.7%
	7.50^0	44.2%	41.5%	2.7%

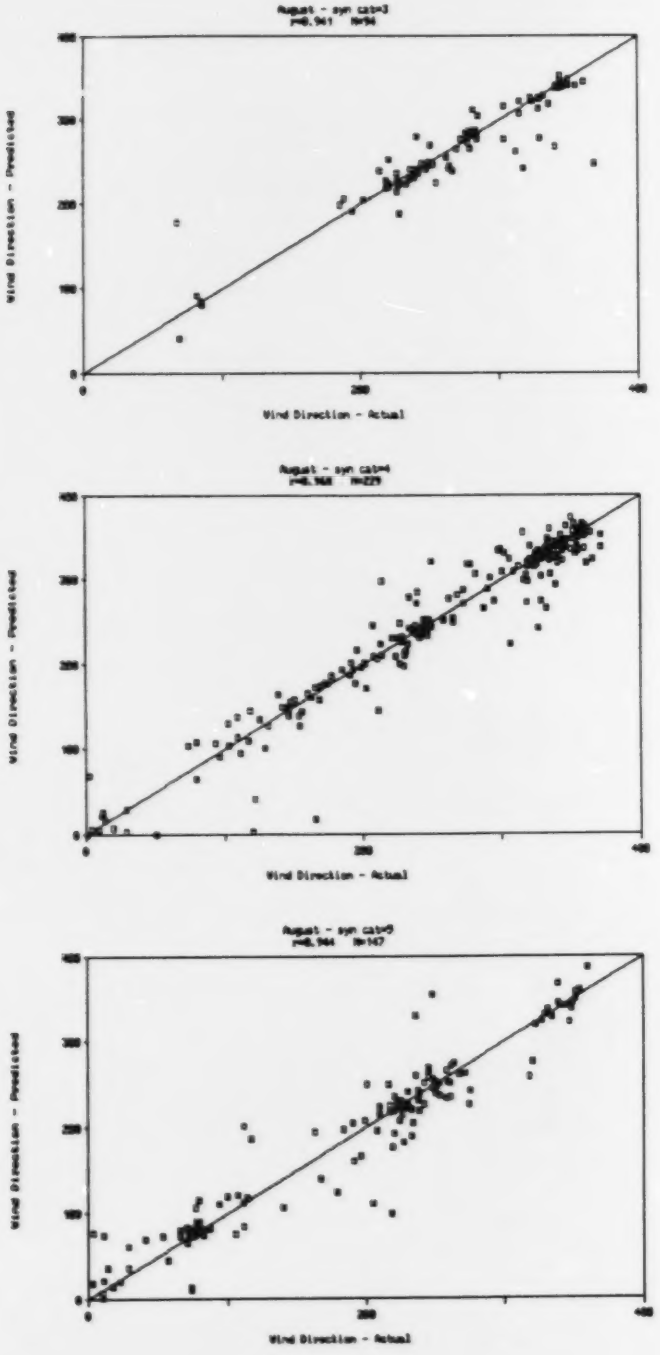
[1] Number of points

[2] A prediction is termed a success if the difference between the predicted actual values is less than α

TABLE IV - CORRELATION COEFFICIENTS BETWEEN PREDICTED AND ACTUAL VALUES

Synoptic Category	Neural Network Predictor	Persistence Based Predictor
3	94.1%	93.4%
4	96.8%	94.2%
5	94.4%	94.4%

FIGURE 1 - Wind Direction Scatterplots (Predicted vs Actual)


Wind Direction - Predicted
Wind Direction - Actual
Wind Direction - Predicted
Wind Direction - Actual
Wind Direction - Predicted
Wind Direction - Actual